USING SIZE–FREQUENCY DISTRIBUTIONS TO ANALYZE FIRE REGIMES IN FLORIDA

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ABSTRACT

Wildfire regimes in natural forest ecosystems have been characterized with power–law distributions. In this paper, we evaluated whether wildfire regimes in a human-dominated landscape were also consistent with power–law distributions. Our case study focused on wildfires in Florida, a state with rapid population growth and consequent rapid alteration of forest ecosystems and natural fire regimes. We found that all fire size–frequency distributions evaluated in this study were consistent with power–law distributions, but the power–law distributions were piece-wise linear. A kink in the power–law distributions occurred at about 640 ha for flatwoods fires and at about 290 ha for swamp fires. Above these levels, fires "exploded" into a catastrophic regime. If the kink represents the level at which fires become immune to fire suppression effort, we would expect that the location of the kink would occur at smaller fire sizes during extreme fire years due to the increased flammability of fuels and the relative scarcity of fire suppression resources. We found this result for three of four extreme fire years in flatwoods ecosystems and for all four extreme fire years in swamps. These results suggest that catastrophic fires may not be possible to prevent and that suppression efforts during extreme fire years may be best applied to strategic areas that decrease the connectivity of fuels.

keywords: fire regime, fire suppression, Florida, power–law distributions, self-organization, size–frequency distribution.

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INTRODUCTION

The catastrophic wildfires that occurred in Florida during the summer of 1998 were the worst in terms of area burned in at least a half-century (Barnett and Brenner 1992). In northeast Florida alone, approximately 202,430 ha burned and produced economic losses of at least $600 million (Butry et al. 2001). Although there is some recent empirical evidence that catastrophic wildfire seasons in Florida are related to the El Niño–Southern Oscillation phenomenon (Brenner 1991, Prestemon et al. 2002), the broad-scale characteristics of fire regimes over time and space are not well understood. As human populations increase in the urban–wildland interface, it becomes increasingly important to understand the nature of wildland fire regimes and how they are affected by human actions such as fragmentation of wildlands, prescribed burning, and fire suppression.

Recent attempts to characterize forest fire regimes have been developed using a theory known as "self-organized criticality" (Drossal and Schwabl 1992). This theory has also been used to describe the dynamics of large interactive natural systems such as avalanches and earthquakes (Bak and Chen 1991). Self-organized criticality is a holistic theory that explains the global features of a dynamic system with parameters that summarize the relative number of small and large events. A key feature of self-organized systems is that the small-scale properties of a system cannot be used to predict large-scale behavior. Rather, large-scale behavior emerges over time and space, resulting from the dynamic interactions between parts of the system.

A widely cited example of self-organized critical behavior is the "sandpile model" (e.g., see Kauffman 1995). In this model, grains of sand are persistently placed in a pile on the top of a table. Over time, the sandpile grows and avalanches of many sizes occur, with an occasional catastrophic avalanche that carries sand off the table to the floor below. However, catastrophic avalanches are initiated by the same event that causes smaller avalanches—the addition of a grain of sand. In this model, a catastrophic cause is not required to induce a catastrophic effect.

An avalanche is a branching process that causes chain reactions through the system. While some avalanches are catastrophic, most avalanches are of small or medium size. The theory of self-organized critical behavior posits that the large-scale behavior of a system over many time steps can be described by a power–law relation:

$$\frac{N_E}{N_S} = A_E^{-\beta}, \qquad (1)$$

where N_E is the number of events, N_S is the number of time steps, A_E is area covered by an event, and β is a parameter describing the power–law relationship. If small events and large events contribute equally to the total area impacted by a series of events, then β = 1. Equation 1 states that there is a negative exponential relationship between the number of events per time period and their size. The negative exponential relationship has been reported for fire regimes in southern California–northern Baja California (Minnich 1983) and the Boundary Waters Canoe Area of Minnesota (Baker 1989).

Forest fires can be thought of as branching processes, and recent empirical analysis has been undertaken to evaluate how consistent historical fire data are with the theory of self-organized criticality (Malamud et al. 1998). In that study, data were obtained for four fire regimes in the United States and Australia: 1) U.S. Fish and Wildlife Service lands (1986–1995), 2) western U.S. (1150–1960), 3) Alaskan boreal forests (1990–1991), and 4) Australian Capital Territory (1926–1991). Malamud et al. (1998) found that forest fires followed a power–law distribution. They reported estimates of β ranging from 1.3 to 1.5, indicating that small fires contributed the most to the total area burned by all fires.

The impacts of human interventions on fire regimes are not well understood, although it is anticipated that humans alter the probability of fire spread both intentionally and unintentionally. Fire spread is affected by fuel connectivity, topography, and flammability of neighboring ecosystems (Christensen 1985). Research in shrubland ecosystems suggests that fire return intervals can be altered by human activities such as road building and agricultural development (Forman and Boerner 1981). Fuel connectivity may also be influenced by fire suppression activity and weather. In a simulation study, Miller and Urban (2000) found that fire suppression increased connectivity under moderate levels of fuel moisture and, consequently, resulted in larger fires. In addition, conditions of very low levels of fuel moisture, as would be present during extreme drought, dramatically increased the risk of large fires in that study, regardless of the spatial distribution of fuel loads. However, in an analysis of fire regimes in California shrublands, Keeley and Fotheringham (2001) concluded that there is no evidence that fire management policies have altered historic fire regimes.

In this paper, we evaluate whether wildfire regimes in a human-dominated landscape are consistent with power–law distributions. Our case study focuses on wildfires in Florida, a state with rapid population growth and consequent rapid alteration of forest ecosystems and natural fire patterns. How successful have fire suppression strategies been in reducing fire spread? How much do catastrophic fires contribute to the total area burned by wildfires in Florida? What strategies are available to fire managers in controlling wildfires in Florida? We address these questions in the analysis below.

STUDY AREA AND DATA

Fire data were analyzed for the entire state of Florida (excluding federal lands) spanning 20 years from 1981 to 2000. Data were provided by the Florida Division of Forestry (DOF) and consisted of operational records for 110,685 fires. However, because we wanted to focus on fires that most closely approached "natural forest" conditions, we only used fire records for forest fires started by lightning. During this time span, about 15% of wildfire ignitions were attributed to lightning (other important ignition sources include arson, debris burning, and cigarettes). Lightning fires are thought to be larger in size, on average, than fires ignited by humans because they generally occur in more remote locations with less road access. Fewer roads serving as firebreaks would be encountered by a spreading fire in these remote areas. Remoteness also would be linked to slower detection and more difficult mobilization of suppression resources.

Florida DOF fire records contained information on a variety of characteristics, including dominant fuel type. Grassy fuels accounted for the greatest proportion of fires in the fire records (about 39%), followed by saw palmetto (*Serenoa repens*, *Sabal* spp.) and gallberry (*Ilex glabra*) (35%), dense pine (*Pinus* spp.) (8%), blowy leaf (7%), swamp (4%), muck (1%), and other (6%). Palmetto–gallberry fires were fires that occurred in the understory of flatwoods pine forests, and "dense pine" fires were crown fires in this forest type. "Blowy leaf" refers to fires in upland hardwood forest types. Swamp fires occurred in baldcypress (*Taxodium distichum*)-dominated stands on sandy soils where organic layers were generally less than 25 cm in depth. Muck fires occurred in swampy areas where organic soils were greater than 25 cm in depth. In this study, palmetto–gallberry and dense pine fuel types were combined to represent "flatwoods."

Fire regimes were evaluated for flatwoods and swamp fuel types. We chose these two fuel types because they allowed us to investigate the hypothesis that fire suppression is less effective during extreme fire years. The parameters describing power–law relationships are altered in years of extreme drought. For example, in the spring and summer of 1998, the Keetch-Byram drought index approached the maximum possible value of 800 for several weeks. We therefore hypothesize that very low levels of fuel moisture resulted in an increase in 1) the area burned by catastrophic fires during that fire season, and 2) the proportion of total area burned that was consumed by catastrophic fires. If this pattern occurred for flatwoods fuel types, this would provide evidence consistent with the hypothesis. If this pattern also occurred for swamp fuel types, this would provide stronger evidence that fire suppression effectiveness decreases in years of extreme drought.

METHODS

Operational fire records obtained from the Florida Division of Forestry contained measurement error because fire sizes were rounded-off during the recording process to correspond with "conventional" fire sizes. Consequently, the frequency of fires for rounded-off fire sizes, such as 10 acres (4.13 ha) or 100 acres (41.3 ha), were typically several orders of magnitude larger than reported fire frequency for neighboring fire sizes, such as 9.9 acres (4.09 ha) or 101 acres (41.7 ha). This procedure created an extreme "sawtooth" pattern in the raw data that was an artifact of the data-recording procedure. Thus, it was necessary to smooth the data prior to data analysis to minimize the impact of these artifacts on subsequent analysis.

Nonparametric smoothing techniques are available that do not impose a parametric functional form on the distribution of data, but rather let the data determine the appropriate functional form (Hardle 1990). In this paper, we used a running-line smoother (Hastie and Tibshirani 1990) based on a local regression:

$$s(x_0) = \delta(x_0) + \gamma(x_0)x_0, \qquad (2)$$

where $s(x_0)$ is the smoothed data for target point x_0, and δ and γ are least squares estimates for the data points in the local neighborhood of x_0. After the value for a target point has been estimated as $s(x_0)$, the smoothed value of an adjacent target point is estimated until all target points have been smoothed. A running-line smoother corrects the first-order bias of a running-mean smoother near the upper and lower limits of the data (Hastie and Tibshirani 1990). This property makes the running-line smoother useful for examining the tails of empirical distributions.

Target points in our data that needed smoothing were observations on fire frequency. Frequencies were computed using SAS software (SAS Institute 2000) by first sorting fire records in ascending order of fire size and then counting the number of fires in each fire size class. Smoothed data points were estimated for each fire size class using Mathcad software (Mathsoft 1991).

To evaluate whether the smoothed fire size–frequency data followed a power–law distribution, base 10 logarithms were computed for fire sizes and smoothed frequencies. Smoothed data were plotted with the logarithm of fire frequency on the *Y*-axis and the logarithm of fire size on the *X*-axis. If fire regimes in Florida followed a power–law distribution, then the plot of fire size and fire frequency in log–log space would result in a negatively sloping straight line. Where this pattern was observed, an ordinary least squares (OLS) regression was performed to estimate the parameters of the power function:

$$\log_{10} N_F = \alpha + \beta(\log_{10} A_F), \qquad (3)$$

where N_F is the number of fires, A_F is fire size, α is a location (intercept) parameter, and β is the slope of the power–law distribution. If a linear pattern was observed over only part of the data range, then an OLS regression was performed over the range(s) of the data that appeared linear. Then, the proportion of the total fire areas explained by the power–law was computed.

Because the area burned in wildfires in Florida is highly variable from year to year, we decided to evaluate three categories of fire size–frequency distributions. First, we estimated the power–law model using all years in the data records. This provided a base line with which to compare other size–frequency distributions and provided an indication of whether the data generally followed a power–law distribution. Second, we estimated power–law models for the most extreme

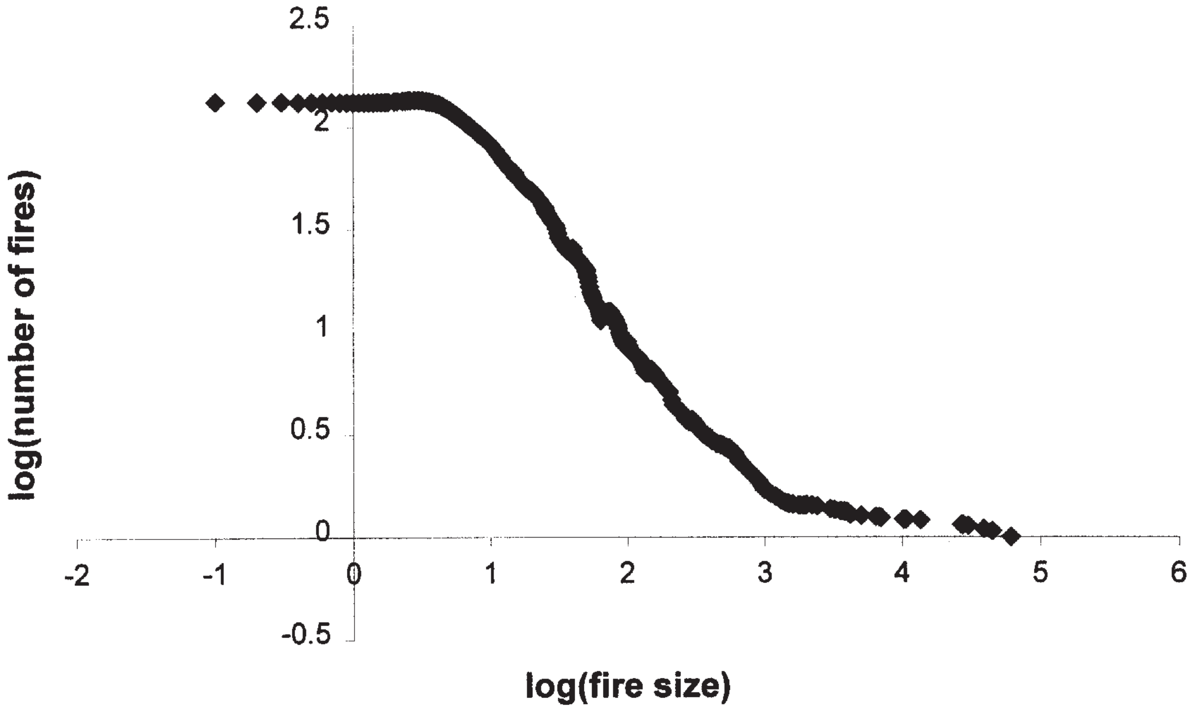

Figure 1. Smoothed fire size–frequency distribution in log–log space for lightning-caused flatwoods fires in Florida, 1981–2000.

fire years in the Florida data: 1981, 1985, 1989, and 1998. Area burned in these years was substantially above average. Examination of the right-hand tail of the size–frequency distributions for these years allowed us to evaluate the hypothesis that catastrophic fires contributed more to the total area burned during extreme years. Finally, we estimated the power–law model for "non-catastrophic" years. This analysis provided an adjusted base line for fire years in the absence of catastrophic fire spread conditions.

RESULTS

All fire size–frequency distributions evaluated in this study obeyed a power–law relationship, but the power–law distributions were piece-wise linear. We discovered that fire regimes in Florida could be broken down into three segments, which we refer to as "small," "moderate," and "catastrophic" segments of the fire regimes. These segments were readily identified in plots of the smoothed fire size–frequency data (Figure 1).

Using the entire data record as an example, small fires are defined by the horizontal segment on the left-hand side of the fire regime and are located in the range from 0.04 to 1.44 ha. This flat segment may be due to under-reporting of small fires or fires that self-extinguish so they are under-represented in the size–frequency distribution. Moderate fires are defined by the downward sloping, roughly linear segment located in the range from 1.44 to about 640 ha. The fire regime again flattens off for fires greater than 640 ha in size. This flattened segment, which we refer to as the "catastrophic" range, includes fires up to 24,940 ha.

Estimates of the slope parameters (β's) associated with moderate fires provide information about the efficacy of fire suppression activities during this period. If fires of all sizes were equally difficult to suppress, then we would expect that the fire size–frequency distribution after suppression would maintain the identical slope of a fire size–frequency distribution prior to fire suppression, although suppression would tend to decrease the value of the vertical intercept (α). However, if the efficacy of fire suppression decreases as fire size increases (large fires are more difficult to suppress), then we would expect that the β's associated with moderate fires would be less than 1 (larger fires contribute the most to area burned), and that this effect would be exacerbated in extreme fire years.

Baseline α's and β's for the entire 1981–2000 period and for the non-catastrophic years provide estimates of "background rates" for fire size–frequency distributions in Florida (Table 1). We note that the

Table 1. Parameter estimates describing power–law relationships in moderate fire regimes, size range of moderate fires, and maximum fire size in catastrophic versus non-catastrophic years, Florida, 1998–2001.

Fuel type	Year(s)	Parameter α	Parameter β	Moderate fire range (ha)	Maximum fire size (ha)
Flatwoods	1981–2000	1.36	–0.83	1.4–642	25,304
	Non-catastrophic years	1.39	–0.88	1.1–486	2,040
	Catastrophic years				
	1998	1.76	–0.61	1.4–202	25,304
	1989	1.64	–0.54	1.4–810	810
	1985	1.67	–0.53	1.4–770	11,174
	1981	1.81	–0.59	1.4–405	12,146
Swamp	1981–2000	0.18	–0.50	0.04–287	8,259
	Non-catastrophic years	0.17	–0.50	0.04–142	3,887
	Catastrophic years				
	1998	0.89	–0.37	0.04–30	8,259
	1989	0.50	–0.22	0.04–8	1,553
	1985	0.49	–0.20	0.04–405	405
	1981	0.50	–0.14	0.04–18	287

background β's were smaller than the slope parameters reported by Malamud et al. (1998), who found that $|\beta| > 1$ (smaller fires contribute the most to area burned) in each of the four fire regimes studied. Background β's in Florida ranged from –0.83 to –0.88 and provide evidence that, even within the moderate range, larger fires contributed more to the area burned than did smaller fires. This result is consistent with the hypothesis that smaller fires are more likely to be controlled than are larger fires.

What happened to the location and slope of the flatwoods fire size–frequency distribution in extreme years? The results showed that α increased relative to the background level (1.36–1.39), indicating an increase in fires of all sizes, and the β's were reduced in size relative to the background rates. Thus, in extreme fire years, catastrophic fires contribute more to the area burned than in non-extreme years. This suggests that, even within the moderate segment of the fire regime, fires become more difficult to fight in extreme fire years.

Does fire suppression become less effective in

Table 2. Total area burned by lightning fires and area burned in the extreme fire regime in catastrophic versus non-catastrophic years, Florida, 1981–2000. Average annual values, for comparison with values for catastrophic fire years, are shown in parentheses.

Fuel type	Year(s)	Total area burned (ha)	Extreme fire regime area (ha)	Percent area in extreme fire regime
Flatwoods	1981–2000	261,930 (13,096/yr)	155,172 (7,759/yr)	59
	Non-catastrophic years	56,646 (3,540/yr)	6,340 (396/yr)	11
	Catastrophic years			
	1998	125,599	116,995	93
	1989	12,438	0	0
	1985	32,231	20,536	64
	1981	34,349	19,445	57
Swamp	1981–2000	21,847 (1,092/yr)	15,824 (791/yr)	72
	Non-catastrophic years	8,214 (513/yr)	5,347 (334/yr)	65
	Catastrophic years			
	1998	9,402	9,401	99
	1989	2,109	2,053	97
	1985	1,220	1,190	98
	1981	1,051	865	82

swamp fires during extreme fire years? According to the β parameter estimates, the answer is "yes" because the contribution of catastrophic fires to total area burned in the moderate region increased in catastrophic fire years (Table 1).

It is quite possible that fires occurring in the catastrophic region represent fires that exceed the capacity for suppression. Under this interpretation of the catastrophic region, suppression appears to be effective up to about 640 ha for flatwoods fires and up to about 290 ha for swamp fires. We note that the size of the moderate fire region shrinks during extreme fire years. This may be due to the fact that increasing fuel flammability promotes rapid fire spread so that fire growth exceeds fire suppression capacity at smaller fire sizes than under conditions less favorable to fire.

How much of the total area consumed by wildfire was burned by fires in the catastrophic region? Table 2 shows that, in non-extreme fire years, only a small proportion of the total flatwoods area burned was in the catastrophic region. Of the extreme fire years, 1989 was unusual because all fires were in the non-catastrophic region. However, in the other extreme fire years, the majority of area burned by wildfires was in the catastrophic region of the distributions.

Swamp fire distributions showed that the majority of the area burned was in the catastrophic region, even in non-extreme years. This is likely because swamp fires are hard to suppress for a variety of reasons including the difficulties associated with operating heavy machinery in those areas. Catastrophic fires consumed almost all of the area burned in swamps during extreme fire years.

DISCUSSION

Lightning-caused flatwoods fires were consistent with power–law distributions, but the power–law distributions were piece-wise linear. A kink in the power–law distributions occurred at about 640 ha for flatwoods fires and at about 290 ha for swamp fires. Above these levels, fires "exploded" into a catastrophic regime.

These results suggest that fires occurring in the catastrophic size range represent fires exceeding the capacity of fire suppression activity. For catastrophic fires, suppression activity may be focused on protecting lives and property rather than on establishing perimeter fire lines. When large fires jump beyond the limits of effective fire suppression, they may resemble fire patterns reminiscent of fire regimes that existed prior to modern fire suppression activity. Gaining a better understanding of the catastrophic fire regime is important as it is the fires in this regime that burn the most acreage in extreme fire years.

In the future, we plan to continue this line of research by 1) examining fire regimes in Florida for other fuel types (such as grasses) and sources of ignition (such as arson), 2) examining the impact of other factors such as weather and forest fragmentation on fire regimes, and 3) studying the characteristics of fires identified as occurring in the catastrophic region using statistical models of extreme value distributions. These studies will enhance our understanding of the nature of fire regimes in Florida and how they are altered by human activity.

MANAGEMENT IMPLICATIONS

Extreme fires may not be possible to prevent. Therefore, fire managers need to recognize the conditions under which extreme fires may occur as well as the locations where they are most likely to occur. Suppression effort may be best applied to strategic areas that decrease the connectivity of fuels during conditions that cause catastrophic fires. This may involve establishing buffers that interrupt fire connectivity during extreme fire seasons.

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